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Dual-domain analysis of CGM data for personalized metabolic health management

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ABSTRACT

Time-domain metrics on a continuous glucose monitoring (CGM) miss hidden dynamics, but frequency-domain features detect up on oscillating patterns, which makes it easier to measure glucose variability and gain clinical understanding. This study aimed to analyze the time and frequency domain features of CGM data for three patients (PtID 65, PtID 109, and PtID 134) to assess glucose variability and control. CGM data were collected over a specified period, with key metrics such as mean glucose, standard deviation (SD), time in range (TIR), and spectral features being computed. The analysis included both time domain and frequency domain features. PtID 109 exhibited the highest mean glucose (207.86 mg/dL) and greatest variability, reflected in the highest SD (85.57 mg/dL) and the lowest TIR (38.24%). PtID 134 showed the most stable glucose levels with the highest TIR (73.60%) and the lowest SD (59.81 mg/dL). Frequency domain analysis revealed that PtID:134 had the highest spectral flatness, indicating more variability in the glucose signal's frequency content. PtID 109 had the lowest TIR at 38.24%, whereas PtID 134 achieved 73.60%, indicating a 24% enhancement and demonstrating superior glucose stability. Dual-domain analysis offers thorough framework for comprehending glucose variability, facilitating individualized treatment and enhanced metabolic health care.

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1. INTRODUCTION

Continuous glucose monitoring (CGM) delivers real-time, high-resolution data on interstitial glucose concentrations, presenting considerable benefits compared to traditional finger-prick testing. By monitoring continuous patterns, CGM facilitates a comprehensive understanding of glucose fluctuation, stability, and overall metabolic regulation. Traditional studies of CGM data frequently priorities time-domain indicators, including mean glucose, standard deviation (SD), and time in range (TIR). These metrics offer therapeutically significant insights into glycemic regulation but may neglect nuanced patterns in glucose variability. To mitigate this limit, researchers have started the investigation of frequency-domain properties, obtained by signal processing methodologies such the fast Fourier transform (FFT). Metrics such as spectral centroid, spectral flatness, and roll-off define the oscillatory characteristics of glucose signals, providing complementary insights on variability. Several studies have associated time-domain features with hypoglycemia risk and treatment results, while recent research on frequency-domain metrics underscores its capacity to uncover hidden dynamics. This study aims to address that gap by examining CGM data from three individuals in both temporal and frequency

domains. The contributions include a dual-domain analytical methodology, comparative patient-level assessment, and clinically pertinent interpretations to inform personalized diabetes care. The objective of our work is to thoroughly examine the role of glucose variability in metabolic health, with a focus on its impact in both diabetic and non-diabetic populations. By exploring the underlying mechanisms that contribute to glucose fluctuation, particularly in type1 and T2D, and evaluating the associated health risks, this study aims to highlight the significance of glucose variability as a critical factor in disease management.

Problem statement: existing research rarely combines time and frequency-domain analysis, limiting a thorough evaluation of glucose variability. Time-domain characteristics lack rhythmic understanding, but frequency-based metrics are less clinically interpretable. This solution integrates both areas for personalized diabetes management. Despite the extensive adoption of CGM, the significance of frequency-domain features in clinical decision-making remains largely investigated. Most studies investigate time-domain and frequency-domain data independently, limiting their collective capacity to thoroughly characterize glucose variability. In real-life scenarios, CGM technology [1] plays an essential role in measuring glucose fluctuations and providing data to improve individual health outcomes. Though the association between CGM-based parameters and adverse kidney outcomes is unclear, a retrospective cohort study of 1,274 type 2 diabetic patients revealed that TIR and glucose coefficient of variation (CV) were substantially connected to chronic kidney disease (CKD) progression, urinary protein deterioration, and mortality from all causes, and the risk of major adverse cardiac events (MACE) [2]. The impact of physical activity on glycemic variability [3] as assessed by CGM in patients with T2D mellitus, was explored the influence of lifestyle factors on glycemic control and variability. Due to the absence of generally recognised athlete-specific reference values, CGM are not yet widely used to assess macular glucose in athletic populations [4]. This research explores into the potential of glucose dynamics measurements, particularly the acceleration and speed of CGM time series, as potential novel biomarkers for predicting glucose outcomes in the long run [5]. To provide non-invasive, continuous monitoring of blood glucose levels at 2.45 and 5.2 GHz introduces a dual-band bandpass filter (DBBPF) [6]. By focussing on certain frequency bands, the sensor improves sensitivity, size, and overall quality. Using data collected from internet of things (IoT) devices, this meta-analysis will assess how well machine learning models can forecast future blood glucose levels [7]. In this work, haemodialysis patients' risk of hypoglycemia is predicted using machine learning algorithms and CGM [8]. Table 1 [9]–[18] (see Appendix) presents the comparative methodology, datasets, and results related to glucose monitoring, variability, and diabetes outcomes.

2. PROPOSED FRAMEWORK MATERIAL AND METHODS

2.1. Study design

The study “CITY: a randomized clinical trial to assess the efficacy and safety of CGM in young adults 14-<25 with T1D” jaeb center for health research. https://public.jaeb.org/ was designed to evaluate the impact of CGM on glycemic control in adolescents and young adults with T1D. Participants, aged 14 to 25, were randomized into groups using either CGM [19] or traditional blood glucose monitoring. Over a 26-week period, key metrics such as mean glucose, SD, TIR, and spectral features were computed. The analysis included both time-domain and frequency-domain features. Each record contains information related to the time, device uploads, and glucose values measured in mg/dL for a specific patient [20]. The study selected three patient identification (PtID)s: 65, 109, and 134, for proof-of-concept validation. PtID 109 had severe hyperglycemia, but PtID 134 demonstrated steady glucose management. PtID 65 showed moderate variability, representing a mid-spectrum case. These profiles enabled comprehensive testing of dual-domain feature extraction under varying situations, highlighting the significance of glycaemic profiles in evaluating control. Figure 1 illustrates the study workflow, commencing with CGM data input, followed by preprocessing, extraction of time and frequency-domain features, comparative analysis across patients and time intervals, and concluding with visualisation and clinical interpretation.

RecID serves as a unique identifier for each record. *PtID* represents the patient’s identification number. *ParentCITY* indicates the city or center from which the data was collected. *DeviceUploadsID* refers to the identifier associated with the device used to upload the data. Date and time when the glucose measurement was taken. Type of record (in this case glucose value measured at the given time (in mg/dL). Unit of the glucose value (mg/dL). Sorting order for the data, possibly indicating the sequence of data collection [21]. CGM data were collected from three participants at fixed intervals. Missing values and sensor artifacts were corrected by interpolation to provide clean, uninterrupted glucose signals for analysis. Out of 100 available data sets, we focused on a detailed discussion of three specific data sets (PtID_109, PtID_134, and PtID_65) from the DeviceCGM CGM data. The process of analyzing and visualizing the provided CGM data set was broken down into the following steps are:

a. Step 1: data preparation involved loading the CGM data and parsing the date and time information from the "DeviceDtTm" field. The data was then organized into a structured DataFrame containing key information such as PtID, glucose values, and corresponding timestamps. The data was divided into daytime and nighttime intervals. Outliers over ±3 SDs were identified and corrected by linear interpolation to provide precise comparisons of circadian glucose variability.
b. Step 2: time domain analysis was conducted by calculating essential metrics, such as the mean glucose level and the SD, to assess glucose variability.
c. Step 3: frequency domain analysis involves applying a fourier transform to the time-series glucose data and time domain visualization, glucose values were plotted over time, highlighting spikes, drops, and overall trends.
d. Step 4: based on this analysis, practical recommendations, such as adjustments in diet or medication, were offered to help manage and stabilize glucose levels more effectively [22].

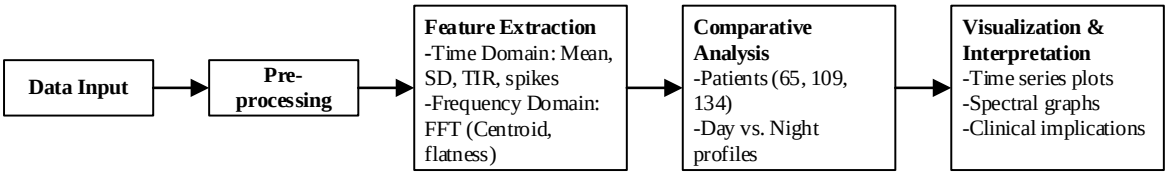


Figure 1. Proposed flow of CGM analysis

2.2. Time domain features

The time-domain features [23] for three patients (PtID 65, PtID 109, and PtID 134) were extracted and analyzed to characterize glucose variability and control. The evaluated metrics include mean glucose, SD, TIR, number of spikes and drops, minimum and maximum glucose, root mean square (RMS), signal power, peak glucose, crest factor, skewness, and kurtosis.

a. Mean glucose: PtID 109 exhibits the highest mean glucose level, indicating a generally higher average glucose concentration compared with PtID 65 and PtID 134.
b. SD: PtID 109 also shows the highest SD, reflecting the greatest variability in glucose levels, whereas PtID 134 has the lowest SD, suggesting more stable glucose control.
c. TIR: PtID 134 achieves the highest TIR, meaning this patient spent the most time within the target glucose range. In contrast, PtID 109 has the lowest TIR, indicating a larger proportion of time outside the desired range.
d. Number of spikes and drops: PtID 109 experienced the highest number of glucose spikes and drops, demonstrating significant fluctuations. PtID 134 recorded the fewest, reflecting more consistent glucose management.
e. Minimum and maximum glucose: the minimum glucose value is identical across all three patients. However, PtID 109 shows the highest maximum glucose level, indicating episodes of severe hyperglycemia.
f. RMS: RMS reflects the overall magnitude of glucose values. PtID 109 has the highest RMS, consistent with its higher mean and variability.
g. Power: signal power, which represents the energy of glucose variations, is also highest for PtID 109, further indicating more intense glucose fluctuations.
h. Peak glucose: PtID 109 exhibits the highest peak glucose level, while both PtID 65 and PtID 134 show peaks of 401 mg/dL.
i. Crest factor: the crest factor, defined as the ratio of peak amplitude to RMS, is used to assess the severity of glucose excursions. A higher crest factor indicates sharper and more extreme glucose spikes.
j. Skewness: PtID 65 has the highest positive skewness, indicating a longer tail toward higher glucose values. PtID 109 shows the lowest skewness, suggesting a more symmetric distribution around the mean.
k. Kurtosis: Kurtosis reflects the peakedness of the glucose distribution and helps identify the presence of extreme glucose events; higher values indicate heavier tails and sharper peaks.

These parameters provide clinically meaningful insight into overall glucose level, variability, and the severities of fluctuations are shown in Table 2.

2.3. Frequency domain features

The FFT was used for calculating spectral centroid, bandwidth, and flatness, therefore capturing oscillatory and rhythmic dynamics that standard glucose variability analysis cannot identify. This suggested that while there were some dominant frequencies, the signal also contained a fair amount of noise or random fluctuations [16].

Table 2. Time domain features extracted

Features	PtID:65	PtID:109	PtID:134
Mean glucose (in mg/dL)	182.35	207.86	152.08
SD	68.79	85.57	59.81
TIR	49.43%	38.24%	73.60%
Number of spikes	223	707	158
Number of drops	154	391	123
Minimum (in mg/dL)	39	39	39
Maximum (in mg/dL)	401	401	401
RMS value (in mg/dL)	194.89	224.78	163.42
Power	37,984.02	50,525.18	26,707.02
Peak (in mg/dL)	401	535	401
Crest factor	2.06	2.38	2.45
Skew	0.50	0.32	0.49
Kurtosis	0.11	-0.62	-0.07

Overall interpretation: PtID 134 demonstrated the highest spectral flatness (0.4472) and the most extensive bandwidth, signifying a larger range of frequency components. PtID 65 exhibited considerable variability, whilst PtID 109 had the lowest flatness (0.4098), indicating a less distributed frequency range. These results correlate with time-domain studies, validating PtID 109 worse glucose management and PtID 134 comparatively more stable glucose regulation is shown in Table 3. All analyses were performed in python (v3.10) utilizing NumPy, Pandas, SciPy, Statsmodels, Matplotlib, and seaborn ensuring repeatability for time-domain, frequency-domain, and statistical analysis with standardised CGM thresholds.

Table 3. Frequency domain features extracted

Features	PtID:65	PtID:109	PtID:134
Peak frequency (Hz)	0.0	0.0	0.0
Spectral centroid (Hz)	-5.23e-06	7.14e-18	-7.13e-18
Spectral bandwidth (Hz)	0.1614	0.1551	0.1630
Spectral frequency (Hz)	Roll-off	Free	-0.0158
Spectral flatness	0.4434	0.4098	0.4472

3. RESEARCH DESIGN AND VISUALIZATION

3.1. Frequency analysis

The frequency domain analysis reveals that while all three patients have a similar low-frequency dominance in their glucose signals, PtID 109 shows stronger low-frequency com-ponents, indicating more pronounced glucose fluctuations. The study highlights the significance of frequency-domain features in diabetes care, highlighting both common and unique patterns. It recognises limitations such as a limited sample size and lack of external validation, proposing for a measured interpretation. Figure 2 illustrates the magnitude and phase spectra for all three patients.

Figures 2(a) and (b) depict PtID 134, whose magnitude spectrum exhibits low-frequency dominance indicative of steady glucose patterns; nevertheless, the irregular phase suggests unexpected fluctuations. Figures 2(c) and (d) illustrate PtID 109, characterized by strong low-frequency components and complex phase spectra, corresponding to increased variability and suboptimal TIR. Figures 2(e) and (f) depict PtID 65, illustrating intermediate glucose variability characterized by moderate low-frequency power and erratic phase dynamics. Interpretation: the integrated magnitude and phase spectra demonstrate individualised glucose variable patterns in patients. PtID 134 has sustained low-frequency dominance, signifying more consistent variations. PtID 109 demonstrates stronger low-frequency components, indicating more variability. PtID 65 displays intermediate characteristics. These discoveries underscore frequency-domain analysis as an auxiliary method for uncovering concealed glucose dynamics and customising personalised therapies.

3.2. Time domain analysis

CGM data for the three patients (PtID 65, PtID 109, and PtID 134) were analyzed based on their glucose levels during periods of least and greatest variation. Target range visualization: the shaded green area between 70 and 180 mg/dL represents the healthy glucose range. TIR calculation: the percentage of time that glucose remained within the TIR was calculated and displayed on the plot. Time and frequency-domain features were calculated for each subject throughout day and night segments. Results were analysed both within and across patients to identify variations in variability, control, and circadian glucose regulation. Analyses were performed in Python utilizing NumPy. The preprocessing criteria adhered to CGM specifications.

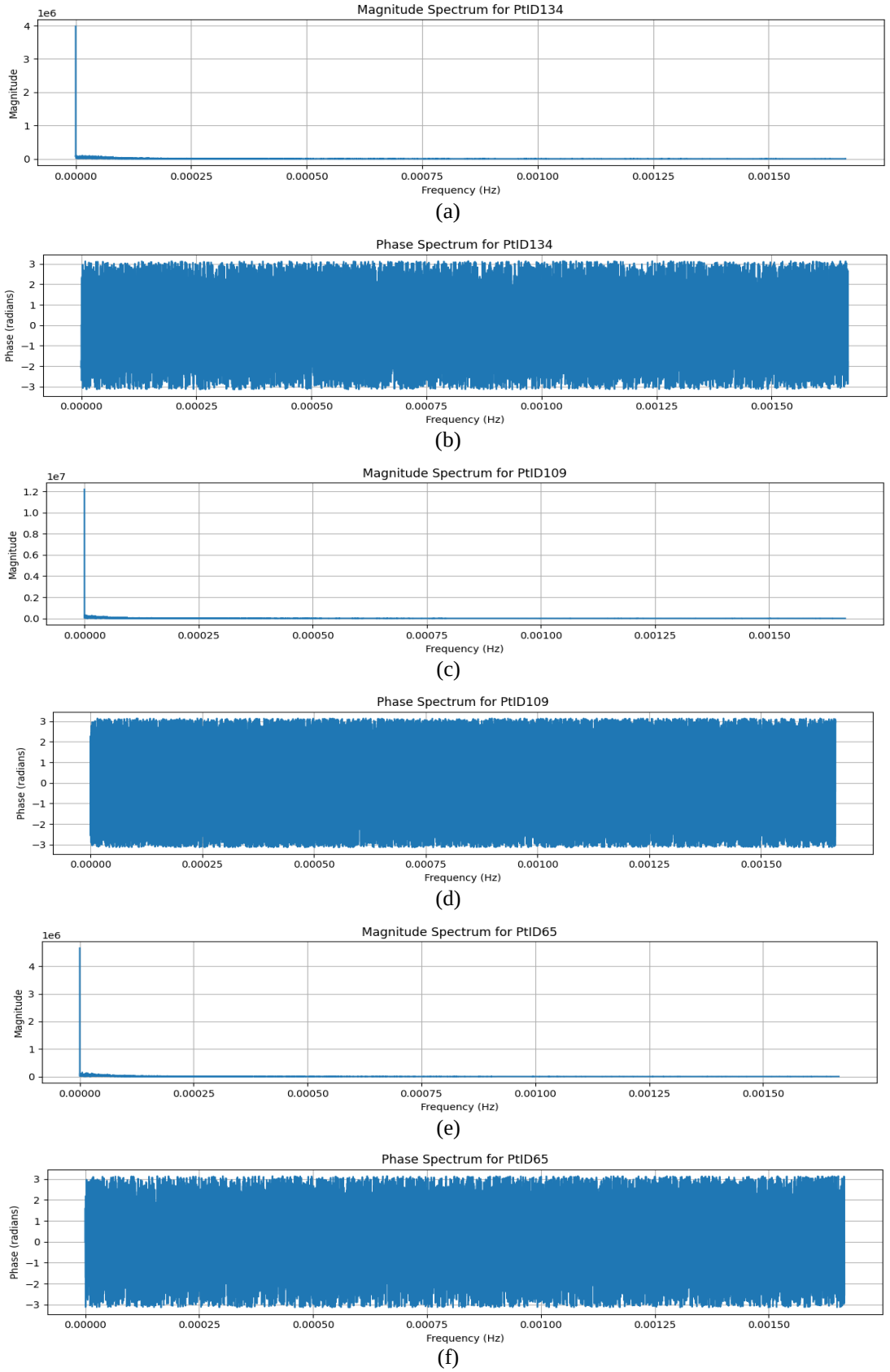
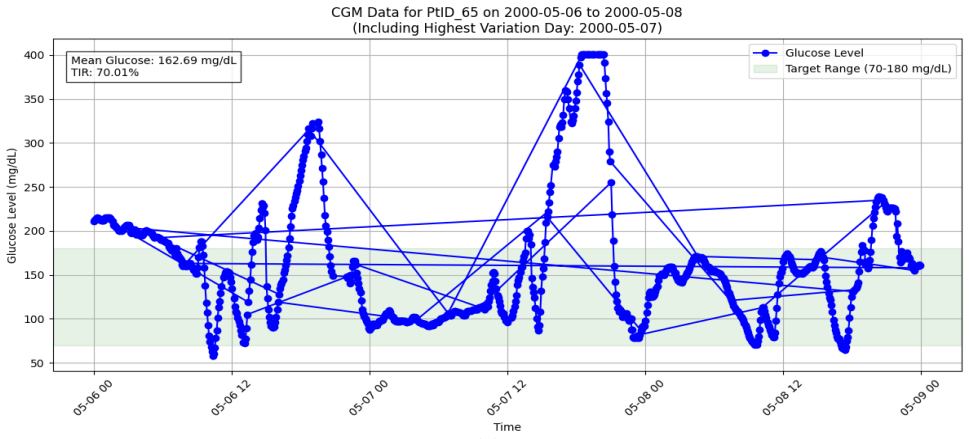


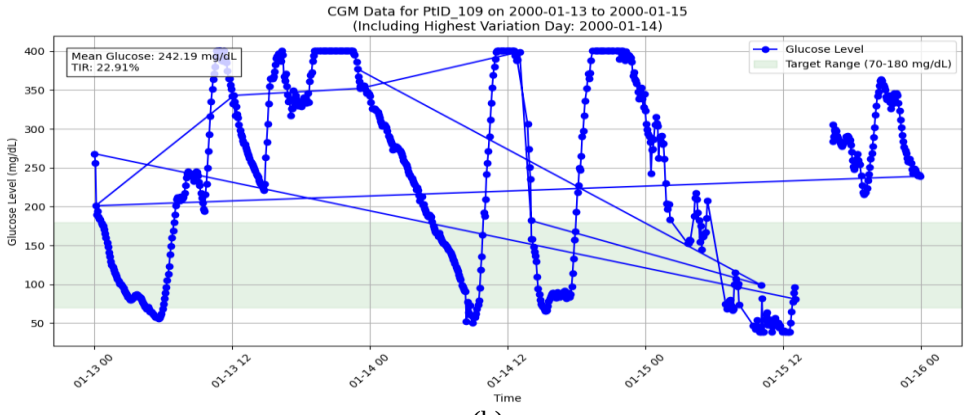
Figure 2. Combination of magnitude and phase spectra for multiple (PtID134, PtID109, and PtID65); (a) magnitude spectrum for PtID 134, (b) phase spectrum for PtID 134, (c) magnitude spectrum for PtID 109, (d) phase spectrum for PtID 109m, (e) magnitude spectrum for PtID 65, and (f) phase spectrum for PtID 65

3.2.1. Period of the highest glucose variability

The visualization of CGM data over a three-day period, specifically from January 13, 2000, to January 15, 2000, revealed key elements of glucose variability. Figure 3 depicts the glucose variability patterns of three individuals demonstrating the most unstable daily profiles. Figure 3(a) for PtID 65 demonstrates fast fluctuations between low and high glucose levels, indicating poor glucose regulation. Figure 3(b) PtID 109 illustrates persistent hyperglycemia interrupted by irregular decreases, signifying considerable metabolic instability. Figure 3(c) PtID 134 exhibits mild yet frequent oscillations, indicating periodic deviations from the normoglycemic range.



(a)



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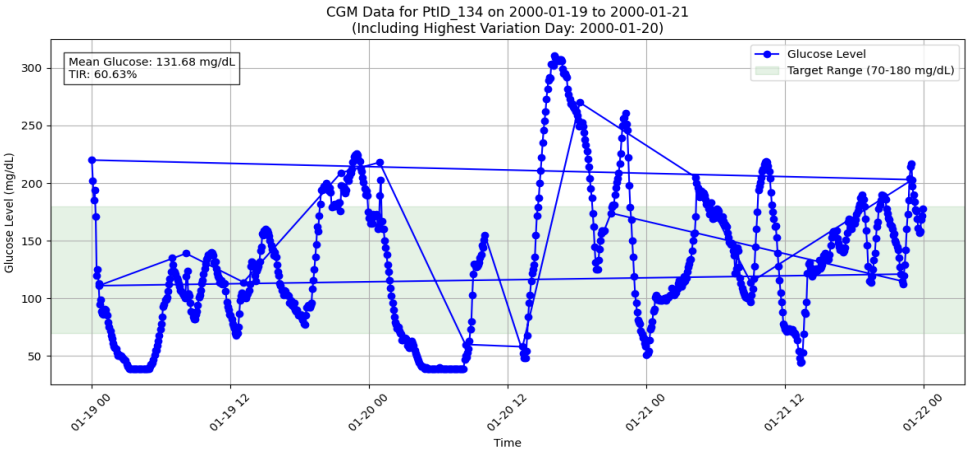

(c)

Figure 3. CGM profiles for patients with the highest daily glucose variability; (a) PtID 65, (b) PtID 109, and (c) PtID 134

3.2.2. Period of the least glucose variability

We compared the CGM data for the three patients (PtID 65, PtID 109, and PtID 134) based on their glucose levels during the period with the least variation. PtID 134 had the most stable glucose levels with the least extreme fluctuations, reflected in their higher TIR and lower mean glucose level. Figure 4 illustrates the CGM patterns for PtID 65, 109, and 134 on days characterised by little glucose fluctuation. Figure 4(a) PtID 65: exhibits predominantly stable glucose patterns with a singular moderate peak, remaining largely within the target range, indicating enhanced glycaemic stability relative to high-variability days. Figure 4(b) PtID 109: shows moderate fluctuations with fewer pronounced spikes or declines, signifying decreased glycaemic instability compared to their typical profile. Figure 4(c) PtID 134: demonstrate the most consistent control, with variations mainly confined to the safe target zone, indicating stable glucose regulation.

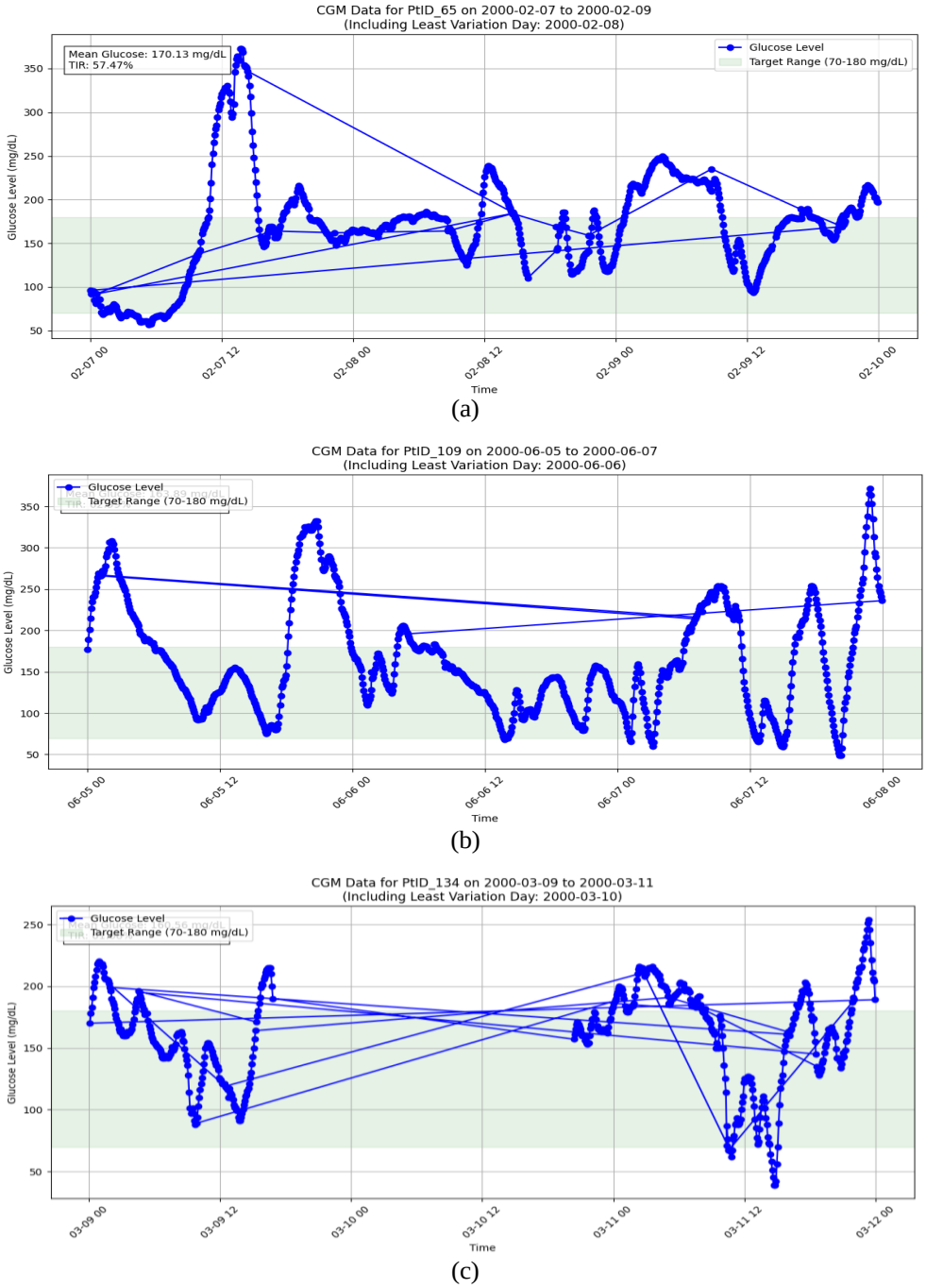

Figure 4. Comparison of CGM data for patients with least glucose variation days; (a) PtID 65, (b) PtID 109, and (c) PtID 134

3.2.3. Period of the highest glucose variability during day and night

To further understand temporal patterns in glucose regulation, the period of highest glucose variability was analyzed separately for daytime and nighttime intervals. Discovering when glucose fluctuations are most pronounced offers valuable insight into patient-specific glycemic behavior, possible treatment influences, and risk periods for hypo- or hyperglycemic events. By examining variableness across different time windows, this analysis highlights critical periods during that glucose control is most unstable, thus supporting targeted treatment and enhanced clinical management.

a. Step 1: identified key dates by finding the day with the highest SD in glucose levels and calculated the day before and the day after this day of the highest variation.
b. Step 2: filtered the data to include only the three-day period around the highest variation day (day before, day of, and day after).
c. Step 3: defined day and night periods.
d. Step 4: separated day and night data by extracting daytime data and nighttime data.
e. Step 5: calculated summary metrics, including the mean glucose level and TIR for both daytime and nighttime and visualized the results by plotting glucose levels over time for both periods, highlighting the target glucose range.
f. Step 6: displayed the results, including TIR and mean glucose, with annotations on the plots showing these metrics for both day and night periods.

The analysis of the CGM data for PtID 109 from January 13 to January 15, 2000, revealed significant differences [24] in glucose levels during daytime and nighttime periods. Nighttime analysis the nighttime glucose levels exhibited [25] even more pronounced issues, with a mean glucose level of 272.28 mg/dL, significantly higher than the daytime mean.

4. RESULTS AND DISCUSSION

4.1. Fast Fourier transform feature analysis

The FFT feature values for PtID 134, PtID 162, and PtID 65 provided insights into the frequency characteristics of their glucose level fluctuations.

a. Spectral flatness: the method overlooks essential features, such as Fourier parameters (window function, segment length, and overlap) and filtering techniques used for signal enhancement. Furthermore, the analysis of only three cases limits generalizability, requiring a rationale for sample selection or an expansion to larger datasets.
b. Spectral roll-off frequency: PtID 134 had a relatively low spectral roll-off frequency, indicating that most of the signal's energy was contained within the lower frequencies. The frequency at which a specific percentage (often 85-95%) of total spectral energy is stored. It represents how quickly signal energy decreases at higher frequencies.
c. Spectral bandwidth: PtID 134 had a moderate spectral bandwidth, indicating a spread of frequency components but not very wide. PtID 162 had a similar spectral bandwidth to PtID 134, suggesting a comparable range of frequency components. PtID 65 showed a similar pattern, with moderate spectral bandwidth, indicating a similar frequency spread.
d. Spectral centroid and peak frequency: PtID 134, PtID 162, and PtID 65 all had spectral centroid and peak frequency values that were close to zero or very low.

4.2. Time domain analysis

PtID 65 performed better during periods of higher variability, managing to keep a lower mean glucose and a higher TIR. PtID 109 showed better glucose control during periods of less variability, with a more favorable mean glucose and TIR. PtID 134 handled glucose levels well even during periods of higher variability, with the lowest mean glucose and a good TIR. The research validates its premise PtID 109 had significant glucose fluctuations and low TIR, whereas PtID 134 demonstrated steady glucose levels and high TIR. Time and frequency-domain analysis demonstrated both general and oscillatory patterns, consistent with previous findings. Limitations include insufficient sample size, short monitoring period, and unconsidered lifestyle factors. Table 4 compares daytime and nighttime glucose data for each patient, presenting the mean, variability SD, and TIR.

The analysis evaluated CGM data from three patients (PtID 65, PtID 109, and PtID 134) utilizing both time and frequency-domain characteristics. The time-domain findings revealed significant variability: PtID 109 showed the highest mean glucose level (207.86 mg/dL), the greatest SD (85.57 mg/dL), and the lowest TIR (38.24%), while PtID 134 exhibited more stability with a smaller SD (59.81 mg/dL) and a higher TIR (73.60%). The TIR for PtID 134 was 24% superior to that of PtID 109, signifying significantly enhanced control. A correlation study showed moderate relationships between SD and spectral centroid (r=0.52) and

between TIR and spectral flatness (r≈0.61), indicating that frequency features significantly enhance time-domain analysis. ANOVA testing indicated that mean glucose and TIR values demonstrated significant variations across individuals ($p<0.05$). Pairwise t-tests indicated that PtID 109 showed a significant difference from PtID 134 in both mean glucose and TIR ($p<0.01$).

Table 4. Comparison of daytime and nighttime glucose metrics for each patient

PtID	Period	Mean glucose (mg/dL)	SD (mg/dL)	TIR (%)
134	Day	130.88	59.81	73.60
134	Night	132.43	62.12	48.72
65	Day	146.03	68.44	79.81
65	Night	179.55	75.32	60.10
109	Day	201.34	82.21	41.35
109	Night	214.12	85.57	38.24

PtID 134 has elevated spectral flatness and reduced spectral centroid, indicating enhanced stability, and a decreased potential of severe glucose variations, so aiding clinicians in distinguishing patients with more stable profiles. PtID 134 and 65 showed robust daytime glucose regulation; however, they had reduced stability throughout the night, characterised by decreased TIR and elevated mean glucose levels. PtID 109 frequently shows insufficient control, highlighting the necessity for personalised modifications to enhance metabolic health. The limited sample size of the research and lack of contextual data restrict generalizability, while frequency-domain features require validation in larger cohorts for therapeutic use. Future study should explore the integration of day-night analysis with frequency-domain measures to capture circadian variations, facilitating predicting tools for nocturnal instability and informing targeted therapies.

5. CONCLUSION

The analysis of CGM data across different patients revealed significant variability in glucose control between daytime and nighttime, with some patients showing better management during periods of less variation. PtID 134 showed the best overall glucose control, especially during the day, but could have benefited from improved nighttime management. PtID 109 had the most challenging glucose control issues, with significant hyperglycemia during both day and night, requiring immediate attention to reduce health risks. PtID 65 managed glucose levels well, particularly during the day, with nighttime management also being relatively effective, though slightly less controlled. The research indicated that integrating dual domain elements in CGM data yields a more thorough comprehension of glucose changes. It demonstrated steady control in PtID 134, excellent daytime regulation in PtID 65, and inadequate overall management in PtID 109. Future works include the integration of machine learning models for predictive analytics, the expansion of analysis to non-diabetic populations, the exploration of long-term patterns, and the integration of spectral data for real-time feedback systems aimed at proactive glucose control.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Selvaraj Gowriswari	✓	✓	✓			✓	✓	✓	✓				✓	✓
Saminathan Brindha	✓	✓		✓	✓			✓		✓	✓	✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created.

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APPENDIX

Table 1. Literature comparison

Ref	Methodologies	Datasets	Findings
[9]	This research included 64 voluntary T2DM patients, evaluating 24-hour ECG, metabolic function parameters, sleep quality, and sleep staging outcomes.	Only data from 60 male inpatients were used in the follow-up tests.	The research identified substantial relationships among sleep quality, 24-hour wake-sleep cycles, heart rate variability, and clinical metabolic function markers.
[10]	The CGMformer is a deep learning model of CGM information to precisely depict an individual's intrinsic metabolic condition for medical use.	It demonstrates generalisability in imputing glucose values across five external datasets encompassing diverse demographics and metabolic conditions (MAE=3.7 mg/dL).	CGMformer is a deep learning model developed using extensive CGM data to analyse individual glucose dynamics for therapeutic purposes.
[11]	The research examined two weeks of CGM data from 5,901 adult patients.	With type 2 diabetes were retrieved from a clinical database Chennai, India, establishing profiles, and investigating their correlation with existing problems.	Three glycaemic variability patterns were identified utilizing CGM data: TIR, Hypoglycemia, and Hyperglycemia.
[12]	Continuous monitoring of blood glucose levels in ICU patients enhances outcomes.	The complexity of the data was analysed using detrended fluctuation analysis and multiscale entropy (MSE) approaches.	Recordings were divided into 24-hour intervals, and MSE analysis indicated variations in entropy, enabling periodic evaluations of BG signal complexity.
[13]	The research examined influence of overnight glucose on seven next functional outcomes in adults with type 1 diabetes.	Out of 196 subjects who started the research procedure, 12 lacked interpretable CGM data, and 21 had fewer than 7 days of concurrent EMA and CGM data.	A overnight CV and time above 250 mg/dL are important predictors of subsequent daily performance, with an elevated CV correlating with less sustained attention.
[14]	The research investigates glucose regulation from normoglycemia to dysglycemia by CGM measures and formulates a machine learning-based classification model for dysglycemia.	Five CGM trials with at least two days of data were combined. Healthy, prediabetic, and type 2 diabetic participants participated.	A study including 836 participants showed a gradual transition in CGM indices from healthy individuals to those with diabetes-related conditions.
[15]	To investigate the glucose profile of Chinese individuals with type 1 diabetes (T1D) who also have metabolic syndrome.	In Jan, data from the CGM, utilizing the revised NCEP-ATPIII criteria, was gathered and analysed between people with and without metabolic syndrome.	Participants with metabolic syndrome were older and had extended durations. CGM measures indicated elevated time over range, SD, and interquartile range in individuals with metabolic syndrome.
[16]	Evaluate the suitability of the CV and SD as indicators of glucose variability (GV) relative to mean glucose (MG) levels in persons with type 1 diabetes.	The data from the GOLD and SILVER trials were analysed.	A study including 158 persons revealed a nonlinear correlation between glucose levels and MG during CGM and self-monitoring of blood glucose (SMBG).
[17]	An advanced system that monitors and assesses the walking patterns of diabetic patients with wearable IoT sensors integrated with artificial intelligence (AI).	Uses wearable sensors to gather real-time data on stride length, gait velocity, and pressure distribution, identifying minor trends that may signify diabetes-related complications.	AI technology enhances diabetes care by delivering personalised recommendations and prompt feedback on walking patterns, facilitating continuous monitoring and regulation of diabetic health.
[18]	A 24-week randomised controlled study involving 40 overweight persons with impaired glucose tolerance (IGT) or type 2 diabetes mellitus (T2DM) to modify body weight during the intervention period.	It used FreeStyle Libre and FreeStyle Libre Pro sensors in an outpatient environment, gathering data at the data centre and each study location.	A study comparing 19 participants in the isCGM group to 20 in the control group revealed a substantially elevated baseline BMI in the isCGM group.

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